DOCUMENT RESUME

ED 263 734 EC 181 306

AUTHOR Ferrara, Joseph M.; And Others
TITLE Class 2: An Expert System for Student Classification. Technical Paper.
PUB DATE May 85
NOTE 22p.; Paper presented at the Annual Meeting of the American Association on Mental Deficiency (109th, Philadelphia, PA, May 27-31, 1985). Prepared at the Artificial Intelligence Research & Development Unit, Developmental Center for Handicapped Persons, Utah State University.
PUB TYPE Reports - Descriptive (141)

EDRS PRICE MF01/PC01 Plus Postage.
DESCRIPTORS *Artificial Intelligence; *Decision Making; *Disabilities; Elementary Secondary Education; Learning Disabilities; Special Education; *Student Placement
IDENTIFIERS *Expert Systems

ABSTRACT

The paper describes an approach to developing systematic procedures for identifying handicapped children that leads to rational decisions regarding placement. An expert system is described which involves the user in a dialogue on data regarding individual children; this dialogue is similar in many ways to a consultation with an expert. After collecting the information, the computer program combines facts and rule-based logic to produce a solution. The system has components for learning disabilities, speech and language, mental retardation, behavior disorders, physical impairment, and sensory impairment. Examples are cited of the learning disabilities component, which contains a knowledge base of over 170 rules. Examples illustrate procedures to test rules and to end the consultation. Additional features of the system include abilities to track and monitor computer logic as the program attempts to determine advice and to query the program at any point in the consultation regarding its intermediate conclusion. (CL)

**********
* Reproductions supplied by EDRS are the best that can be made *
* from the original document. *
**********

U.S. DEPARTMENT OF EDUCATION
NATIONAL INSTITUTE OF EDUCATION
EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)
This document has been reproduced as received from the person or organization originating it.
Minor changes have been made to improve reproduction quality.
• Points of view or opinions stated in this document do not necessarily represent official NIE position or policy.

ED263734

# Technical Paper

## CLASS 2: An Expert System for Student Classification

**Joseph M. Ferrara**
**James D. Parry**
**Margaret M. Lubke**
**May, 1985**

**Artificial Intelligence Research & Development Unit**
**Developmental Center for Handicapped Persons**
**Utah State University**
**Logan, Utah 84321**

EC 181306

BEST COPY AVAILABLE

"PERMISSION TO REPRODUCE THIS MATERIAL HAS BEEN GRANTED BY
Joseph M Ferrara
TO THE EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)."

Paper Presented at the Annual Convention

of the

American Association of Mental Deficiency

109th, Philadelphia, PA, May 27-31, 1985

CLASS.2: An Expert System for Student Classification

Multidisciplinary teams must make decisions regarding the identification of handicapped children and their eligibility for special education services. Research on the functioning of such teams has indicated that they do not follow a systematic approach in making such decisions. Furthermore, many of the judgments made by multidisciplinary special education placement teams have not been accurate. This inaccuracy accounts, in part, for the 84 percent increase in the number of pupils identified as learning disabled during the past few years (Hofmeister, 1983). Ysseldyke (1983) contends that at least half of the number of identifications in the area of learning disabilities may be inaccurate.

Research examining team decision-making processes is no less disturbing. A great deal of data describing student performance is collected, but much of it is technically inadequate and irrelevant (Thurlow & Ysseldyke, 1979). Teams spend about 30 percent of their time discussing these questionable data (Ysseldyke, Algozzine, Rostollan, & Shinn, 1981). Furthermore, individuals discussing these data are likely to use language which is unfamiliar to noneducators (Ysseldyke, 1983). Considering this unfortunate state of affairs, it is not surprising that Ysseldyke, Algozzine, Richey, and Graden (1982) reported that there was little relationship between the psychometric data presented to placement teams and the eligibility decisions those teams made.



BEST COPY AVAILABLE

Examples of Placement Team Dysfunction

A number of reasons have been suggested for placement teams' apparent inability to make consistently accurate decisions. Generally, there appears to be no systematic approach to eligibility determination. This lack of organization can result in several specific types of team dysfunction. Two examples of team dysfunction are "a priori decision making" and "aggressive ignorance."

A priori decision making. Frequently, placement decisions are made prior to the actual team meeting by a few supposedly "knowledgeable" individuals. Team members are then presented with technically inadequate, irrelevant, and incomprehensible information describing the child (Thurlow & Ysseldyke, 1970; Ysseldyke, 1983; Ysseldyke, Algozzine, Rostollan & Shinn, 1981). Following this presentation, the team is asked to support the placement decisions which have been made prior to the meeting (Alpert & Trachtman, 1980). Teachers and other professionals rarely argue with the a priori decision or make suggestions about what should be done with the student (Ysseldyke, Algozzine & Allen, 1981).

If the determination of program eligibility was easy, then the "rubber stamp" behavior of confirming a priori decisions might be acceptable. Unfortunately, the basis for eligibility decisions is not clear cut. For example, judgments about the validity of a test or observations of student classroom behaviors are certainly subject to personal bias and often open to professional debate. Although state and federal regulations are meant to clarify eligibility decisions, they often exhibit little

logic and frequently provide limited information for determining eligibility (Patrick & Reschly, 1982; Sabatino, 1983).

Aggressive ignorance. A second type of team dysfunction can be described as aggressive ignorance. In this situation, an aggressive individual might convince team members to ignore selected portions, or in some cases, all psychometric data. In one extreme case, an administrator has reported that his school had no mentally retarded students, no students with behavior disorders, and that about 30 percent of the student body was learning disabled. It was later found that the error resulting in this unlikely distribution of students could be traced to the misconceptions of one strong individual who attended all of the district's team meetings (Ferrara, Miller, Monroe & Thompson, 1983).

## Effect on Children

When placement teams do a poor job of applying eligibility criteria, handicapped and nonhandicapped children are not well served. If, for example, large numbers of nonhandicapped children are identified as learning disabled, those children receive inappropriate treatment. In addition, less money remains to serve children who are in need of special education services (Sabatino, 1981).

Another unfortunate result of inappropriate eligibiilty decision making has been the establishment of rules which set an arbitrary limit on the number of handicapped children a school can report for funding (Sabatino, 1981). Such rules subvert the intent of P.L. 94-142 in that they discriminate against

handicapped children who happen to live in schools with an unusually high handicapped population. At the same time, these rules encourage aggressive and "imaginative" administrators in districts with a low percentage of handicapped students to find "handicapped" students to fill their "quota" and obtain additional funding.

Expert Systems: A Potential Solution

Special educators are faced with the problem of developing systematic approaches to identifying handicapped children that lead to rational decisions regarding placement. The CLASS.2 system addresses this problem through the application of recent developments in computer software (specifically, artificial intelligence). An artificial intelligence (AI) system can help to provide a systematic approach to the student placement decision-making process. Furthermore, AI systems can be used to provide preservice students with training and practice in making placement decisions.

> Artificial intelligence (AI) is the art of computer science concerned with designing intelligent computer systems, that is, systems that exhibit the characteristics we associate with intelligence in human behavior--understanding, language, learning, reasoning, solving problems, and so on. (Barr & Feigenbaum, 1981, p. 3)

Applications of artificial intelligence which seek to replicate decision making by knowledgeable and experienced humans are called expert systems. An expert system typically engages the user in a dialogue. This dialogue parallels, in many ways,

the type of conversation a person might have with an expert consultant. The computer is programmed to ask the user questions to detail the problem or situation (Barr & Feigenbaum, 1981). In the decision-making processes about eligibility for special education services, these questions would regard data on the child who is being considered. After collecting this information, the computer program combines the facts and rule-based logic to produce a solution to the user's problem--in this case, the appropriateness of special education classification and services (Hofmeister & Ferrara, in press; Stefik, Aikins, Balzer, Benoit, Birnbaum, Hayes-Roth & Sacerdoti, 1983).

Expert systems have been used effectively in training and inservice settings. For example, a well-known medical system that led to instructional applications is MYCIN (Davis, Buchanan, & Shortliffe, 1975). With the MYCIN program, the user enters into the computer, information on the characteristics of the patient's bacterial cultures and present symptoms. The computer then matches the patient's data with information in the program on the characteristics of bacterial cultures, and based on programmed logic, arrives at a disease diagnosis. In its initial form, MYCIN was used in an intelligent computer-assisted instruction program called NEOMYCIN (Clancy & Letsinger, 1981), designed to teach physicians to diagnose bacteriological diseases.

## The CLASS.2 System

The CLASS.2 system applies expert system technology to special education classification problems. The system has six components:

CLASS.LD2 (for Learning Disabilities)

CLASS.SL2 (for Speech and Language)

CLASS.MR2 (for Mental Retardation)

CLASS.BD2 (for Behavior Disorders)

CLASS.PI2 (for Physical Impairment)

CLASS.SI2 (for Sensory Impairment)

Each system component can be used independently to evaluate student eligibility for special education funding in a specific disability area. In addition, the components may be used as a coordinated package for determining student eligibility for services.

Currently, several components are completed and are undergoing final field testing. Other components are in various stages of completion. The discussion and examples which follow are based on CLASS.LD2. The training paradigms employed by CLASS.LD2 are used throughout all six components of the system.

When using CLASS.LD2, the user enters answers to a series of questions regarding a child. Figure 1 shows an example of a typical consultation with CLASS.LD2.

CLASS.LD2 contains a knowledge base of over 170 rules. During a consultation, the program uses these rules to determine which questions to ask and, ultimately, which conclusions to infer. Figure 2 shows an example of one such rule.

What test was used to measure the student's level of intellectual functioning?

WISC–R
WAIS
Stanford–Binet
Bayley Scales of Infant Development

*>> wisc*

What is the student's most recent IQ score?

*>>70*

What is the student's age in months?

*>>120*

Figure 1. Examples of consulting using CLASS.LD2.

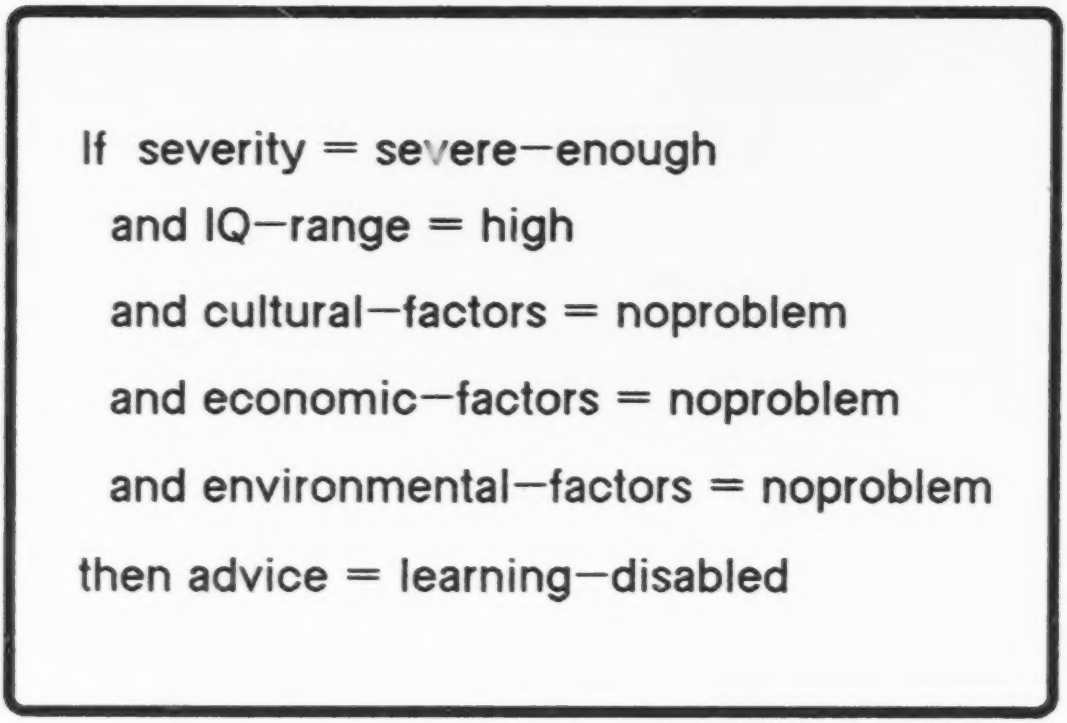
If severity = severe—enough
and IQ—range = high
and cultural—factors = noproblem
and economic—factors = noproblem
and environmental—factors = noproblem
then advice = learning—disabled

Figure 2. Example of rule from CLASS.LD2 concluding advice

The rule in Figure 2 can be translated as follows: If the discrepancy between predicted and actual student performance is severe enough, and the student's IQ is high (no more than one standard deviation below the mean), and there are no cultural, economic, or environmental factors which would preclude an LD label, then advise the user that this is a learning disabled child.

If all of the conditions stated in a rule are true, then the rule succeeds. CLASS.LD2 utilizes backward chaining to determine if rules succeed. When testing the rule in Figure 2, for example, CLASS.LD2 would first seek a value for the expression, "severity," then values for the expressions "IQ-range, cultural factors, economic factors, and finally, environmental factors," will be sought.

There are three ways for the system to obtain a value for an expression: (1) check global memory; (2) try rules concluding with the expression; and (3) ask the user. These are shown in Figure 3.

Figure 4 shows how CLASS.LD2 tests a rule designed to identify invalid IQ test scores. Specifically, this rule determines if the particular IQ test is valid for individuals in the students' age range. A numerical sequence is presented in Figure 4, showing the procedures used to test this rule. The following descriptions accompany the procedures:

1. Seeks a value of the expression "test-age" by using a rule which concludes with "then-test-age."

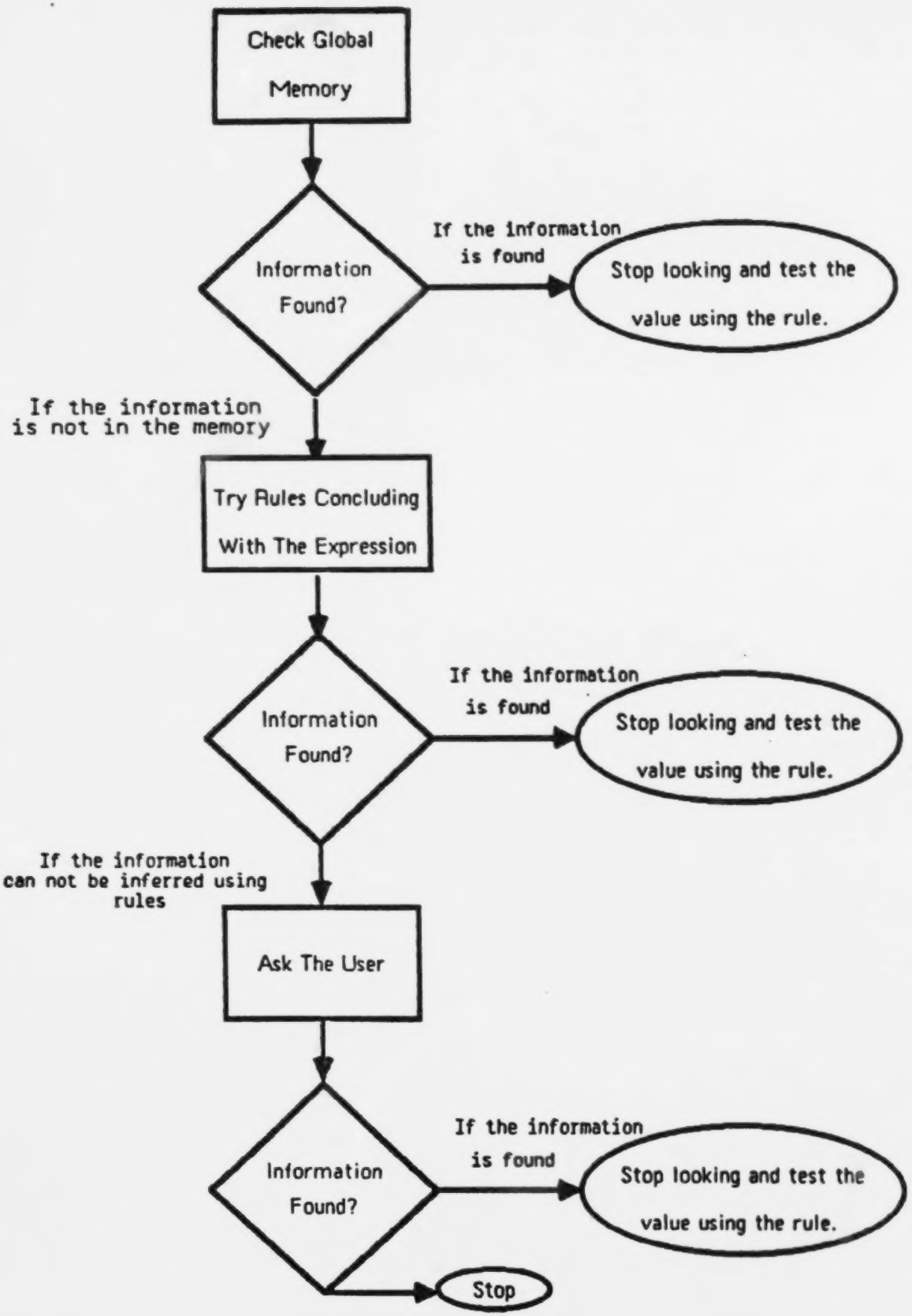
Check Global Memory
Information Found?
If the information is found
Stop looking and test the value using the rule.
If the information is not in the memory
Try Rules Concluding With The Expression
Information Found?
If the information is found
Stop looking and test the value using the rule.
If the information can not be inferred using rules
Ask The User
Information Found?
If the information is found
Stop looking and test the value using the rule.
Stop

Figure 3. Three ways to obtain a value for an expression.

BEST COPY AVAILABLE

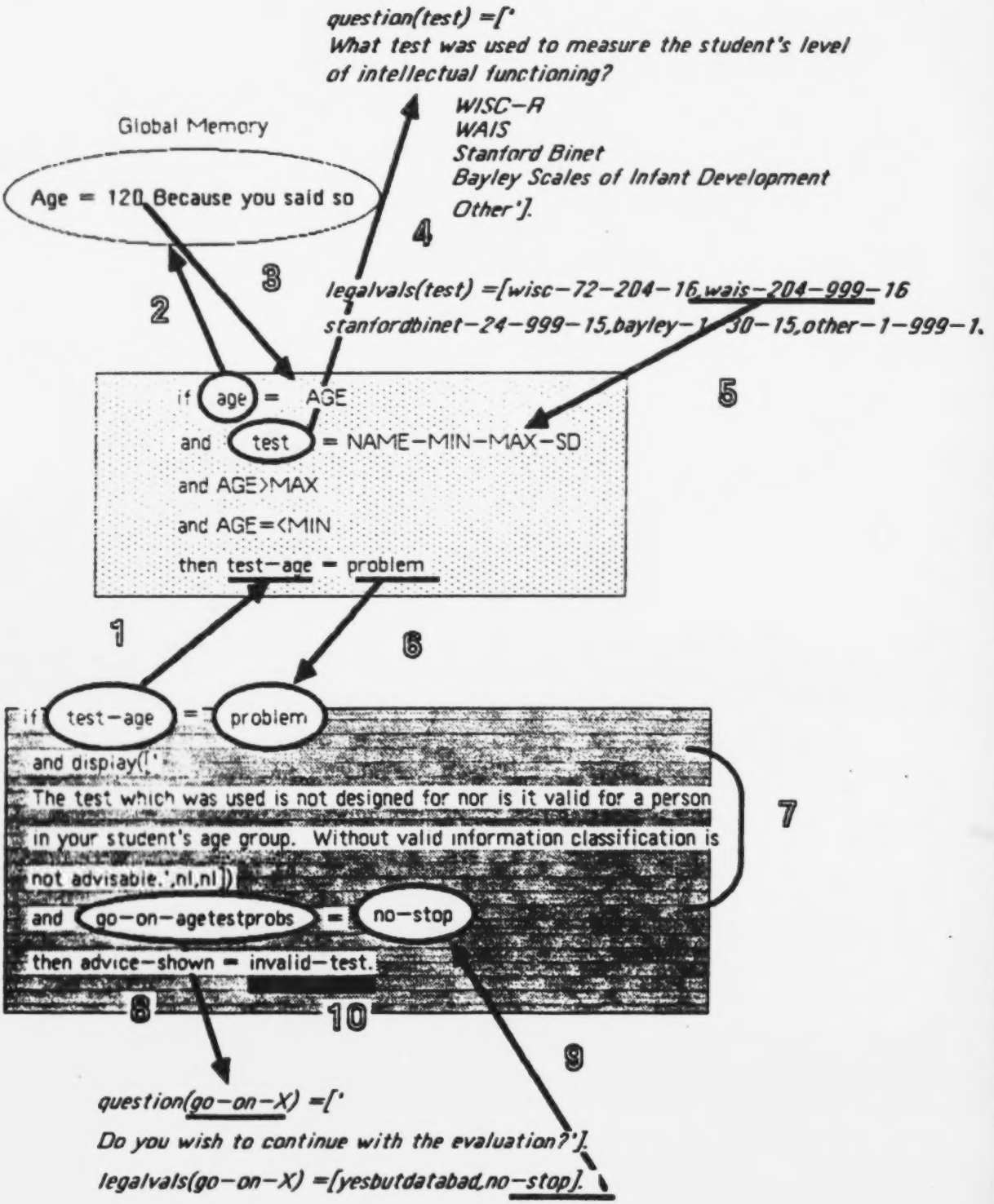


Figure 4. Example illustrating how CLASS.LD2 tests a rule.

2. Seeks a value for the expression "age" in the global memory (location for information already known by the system).
3. Returns 120 as a value for "age."
4. Seeks a value for the expression "test" by questioning the user.
5. Returns the user's value WAIS-204-999-16 as the value for "test."
6. The rule succeeds and the value "problem" is returned for "test-age."
7. The message included in the rule is displayed to the user.
8. Seeks a value for the expression "go-on-agetest probs" by asking the user.
9. Returns the user's value "no-stop" for "go-on-agetest probs."
10. The rule succeeds and the expression "advice-shown" is given the value "invalid-test."

There are three ways in which a CLASS.LD consultation can be ended.

The "quick-out." In a "quick-out" situation, CLASS.LD2 identified a condition which totally precludes the possibility of the child being classified as learning disabled. Figure 5 shows a rule which results in a "quick-out." In the "quick-out" shown in Figure 5, CLASS.LD2 does the following:

1. Seeks to find a value for the expression "area" by asking the user a question;

BEST COPY AVAILABLE

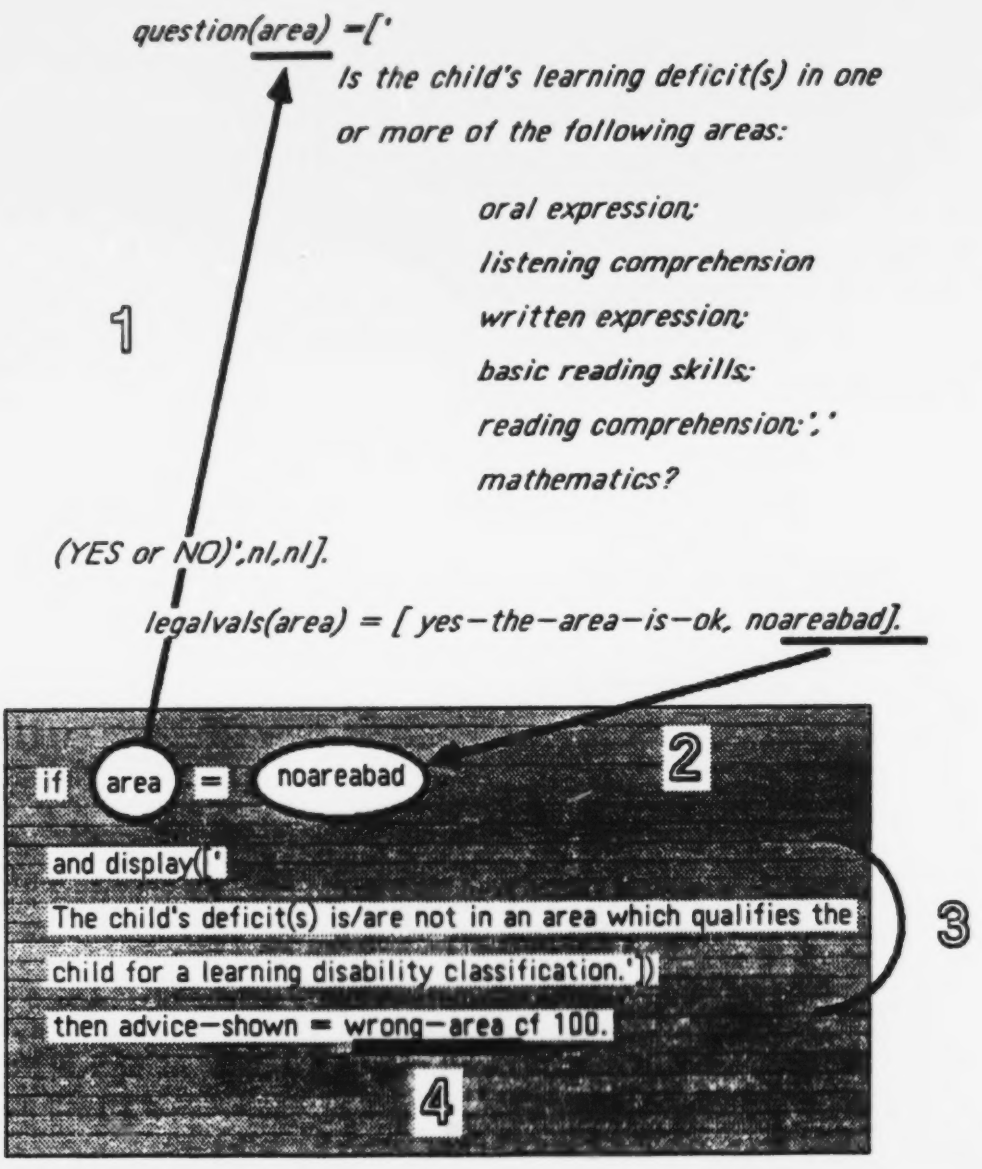


Figure 5. Example of a rule from CLASS.LD2 illustrating a "quick-out."

2. The value of the user's response "NOAREABAD" becomes the value of the expression "area;"
3. The message imbedded in the rule is printed on the screen to have the value "wrong-area."

The "voluntary-end." In a "voluntary-end" situation, CLASS.LD2 establishes that the information provided by the user is too limited to determine a valid classification about learning disabilities. Thus, if the rule shown in Figure 4 succeeds, the consultation results in a "voluntary-end."

"Advice shown." When the system collects enough information to provide reasonably reliable advice, that advice is displayed on the computer monitor and the consultation ends. The rules involved in a consultation leading to "advice shown" are somewhat more complex than those shown for the "quick-out" and "voluntary-end." Figure 6 shows an example of the system's display associated with an "advice-shown" outcome. Section A of Figure 6 includes three pieces of advice displayed to the user. Section B of the figure includes the level of certainty which may be attached to each element of the advice.

## Additional Features

The M.1 authoring system used to create CLASS.LD2 has several features which make the system particularly attractive to educators.

1. The "TRACE" facility allows the user to track and monitor the computer logic as the program attempts to determine advice.

A. Bad-data:

The information given is questionable, and classification based upon the data provided is probably illegal because of missing or invalid information.

Learning-disabled:

If the information which you have provided is correct, the child may be classified as learning disabled at the confidence level suggested below.

Emotional-problems:

A child with serious emotional problems cannot be classified as learning disabled. This child may be considered for a behavior disorder program.

B. advice-shown=bad-data (99%) because kb-33.
advice-shown=learning-disabled (66%) because kb-33.
advice-shown=emotional-problems (30%) because kb-33.

Figure 6. Example of CLASS.LD2 output for "advice shown."

2. The "WHY" facility allows the user to inquire about "why" the program asked a question. The machine's response might include an M.1 rule, an English translation of an M.1 rule, or a reference to state and/or federal law.
3. The "SHOW" facility allows the user to query the program at any point in the consultation regarding its intermediate conclusions.

The CLASS.2 system, of which CLASS.LD2 is a part, is currently undergoing field testing in three states. When completed, we believe the system may provide an effective and inexpensive solution to many misclassification problems. In addition, the Artificial Intelligence Research and Development Unit at Utah State University has begun work on an intelligent tutor which uses the CLASS.2 system's knowledge base. This system will provide training for preservice educators and adjunctive personnel. Field testing of the tutor will begin in early 1986.

References

Alpert, J. L., & Trachtman, G. M. (1980). School psychologist consultation in the eighties. (pp. 234-238).

Barr, A., & Feigenbaum, E. A. (Eds.). (1981). The handbook of artificial intelligence, (Vol. 1), Los Altos, CA: William Kaufman, Inc.

Clancy, W. J., & Letsinger, R. (1981). NEOMYCIN: Reconfiguring a rule-based expert system for application to teaching. Proceedings of the seventh international joint conference on artificial intelligence, University of British Columbia, Vancouver, B.C., Canada.

Davis, R., Buchanan, B., & Shortliffe, E. (1975). Production rules as a representation for a knowledge-based consultation program. Report STAN-CS-75-519, Memo AIM-266. Computer Science Department, Stanford University.

Ferrara, Miller, Monroe & Thompson (1983). Adjustments in instruction and curriculum for secondary special education students. Vermillion, SD: University of South Dakota.

Hofmeister, A. M. (March 21, 1983). comments on part B, Section 618: Evaluation and part E, research and education of the handicapped, Public Law 94-142. Testimony before the Senate Committee on Labor and Human Resources, Subcommittee on the Handicapped, Congressional Record. Washington, DC: Government Printing Office.

Hofmeister, A. M., & Ferrara, J. M. (in press). Expert systems and special education. Exceptional Children.

Patrick, J. L., & Reschly, D. J. (1982). Relationship of state educational criteria and demographic variables to school system prevalence of mental retardation. American Journal of Mental Deficiency, 86, 351-360.

Sabatino, D. A. (1981). Are appropriate educational programs operationally achievable under mandated promises of P.L. 94-142? The Journal of Special Education, 15, 9-22.

Sabatino, D. A. (1983). The house that Jack built. Annual Review of Learning Disabilities, p. 23.

Stefik, M., Aikins, JH., Balzer, R., Benoit, J., Birnbaum, L., Hayes-Roth, F., & Sacerdoti, E. (1983). The architecture of expert systems. In F. Hayes-Roth, D. A. Waterman, & D. B. Lenat (Eds.), Building expert systems (pp. 89-126). Reading, MA: Addison-Wesley.

Thurlow, M., & Ysseldyke, J. E. (1979). Current assessment and decision-making practices in model programs for learning disabled students. Learning Disability Quarterly, 2, 15-24.

Ysseldyke, J. E. (1983). Current practices in making psychoeducational decisions about learning disabled students. Annual Review of Learning Disabilities, 31-38.

Ysseldyke, J. E., Algozzine, B., & Allen, D. (1981). Regular education teacher participation in special education team decision making. Elementary School Journal, 82 160-165.

Ysseldyke, J. E., Algozzine, B., Rostollan, D., & Shinn, M. (1981). A content analysis of the data presented at special education placement team meetings. Journal of Clinical Psychology, 37, 665-662.

Ysseldyke, J. E., Algozzine, B., Richey, L., & Graden, J. (1982). Declaring students eligible for learning disability services: Why bother with the data? Learning Disability Quarterly, 5, 37-44.